AI-Powered Online Learning Interaction and Purchase Intention: The Mediating Role of Perceived Enjoyment and Co-Creation

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This research leverages artificial intelligence (AI) technology to propose a novel conceptual framework that examines online learning interaction and consumer purchase intention. The framework integrates Moore's theory of three types of interaction with the co-creation of value theory. Structural equation modelling of data collected from 427 valid questionnaires reveals that AI-powered interactions among learners, content, instructors, and peers significantly enhance users' perceived enjoyment and perceived co-creation, which in turn influence their purchase intention towards online courses. Notably, AI-powered learner-content interaction exhibited a smaller effect on perceived co-creation compared to other forms of interaction, while perceived enjoyment had a markedly greater and differential impact on purchase intention compared to perceived co-creation. These findings suggest that online education platforms and providers should prioritise learner-content interaction in course design and consider the critical role of co-creation in enriching user experiences and fostering purchasing behaviour.

Keywords: AI-Powered; Online Learning; Interaction; Co-Creation; Purchase Intention

Introduction

With the rapid advancement of AI, significant impacts have been observed across various domains, including education, business, management, science, and the economy (Luan et al., 2020). AI technologies have disrupted numerous industries, particularly marketing, by providing advanced tools and insights that enhance efficiency, enable personalisation, and support informed strategic decision-making (Kumar et al., 2024). For example, AI chatbots and voice assistants, capable of replicating human conversational patterns, often achieve higher customer satisfaction than interactions with human employees (Bălan, 2023; Ruan & Mezei, 2022). Furthermore, research suggests that AI endorsers outperform credible human celebrity endorsers in influencing customer purchase intentions. In the field of education, AI tools have been employed on online platforms to enhance teaching efficiency and advance the learning process (Holmes, 2019; Zawacki-Richter et al., 2019). AI-driven personalised video recommendations, for instance, are shown to significantly improve learners' performance and engagement in the learning process. Additionally, AI technologies have proven highly effective in facilitating assessment and feedback processes, while also increasing students' motivation to study (Williamson & Eynon, 2020).

Despite the growing adoption of AI in educational technology (edtech) to improve learning effectiveness and individualisation, limited research exists on AI's influence on learners' purchasing intentions towards such platforms. This represents an opportunity to explore the intersection of AI's business applications and its ability to influence consumer behaviour through education-based platforms. Addressing this gap, the present study proposes a new theoretical framework, grounded in Moore's interaction theory and the value co-creation theory, to examine the impact of AI-driven communication on consumer behaviour. Specifically, it focuses on understanding how AI influences purchasing behaviour within educational contexts, offering fresh perspectives on this emerging field.

Existing research on factors influencing online purchase intention has predominantly focused on traditional e-commerce domains. These studies have highlighted key determinants such as website quality, interactivity, trust, electronic word-of-mouth (eWOM), and online reviews as significant drivers of purchase intention (Harrigan et al., 2021; Sardar et al., 2021; Summerlin & Powell, 2022). More recently, with the continuous evolution of digital technologies, marketing research has shifted its focus towards popular social media platforms, including TikTok, WeChat, and Weibo, to explore consumer purchase intentions. Zhang et al. (2023) found that social interaction on these platforms positively influences consumer intentions by enhancing perceived value. Despite the substantial body of literature on online purchase intentions, there remain notable gaps, particularly in the context of AI. Only a limited number of studies have examined the impact of AI technologies in online shopping environments and their implications for customer purchase intention (Yin & Qiu, 2021). This underlines the need for further research to develop and validate novel theoretical frameworks. Such efforts should not only investigate how AI-driven marketing influences consumer behaviour but also extend these insights to diverse application areas, including financial services, health management, and education (Kumar et al., 2024). Addressing these gaps could significantly enhance understanding of AI's transformative potential in shaping consumer behaviour across multiple sectors.

The cooperative process through which corporations and consumers jointly create value through interaction and participation is referred to as value co-creation. In business and marketing contexts, co-creation signifies a collaborative effort where consumers influence the production process and the final product. It is widely acknowledged that co-creation enhances demand through sustained interaction between consumers and products, thereby generating greater economic value for companies. Recent research on value co-creation has primarily focused on experience sharing on social media and related platforms, particularly in the tourism and hospitality industries (Tregua et al., 2020).

While AI plays a pivotal role in enabling value co-creation, comprehensive studies integrating AI and value co-creation remain scarce (Chandra & Rahman, 2024). Existing attention to the application of AI in co-creation processes is limited. In most cases, the primary antecedents of value co-creation are identified as interaction, participation, and service innovation. However, there is a notable lack of research examining the role of value co-creation as a mediator or moderator variable in such processes (Ribeiro et al., 2023). This underscores the need for further exploration to better understand the interplay between AI technologies and value co-creation dynamics.

Addressing the identified research gaps, this study seeks to examine the impact of AI-powered online learning interactions on consumer purchase intention and to propose a conceptual framework for predicting consumer purchase behaviour in the context of online courses. Specifically, this research aims to: (1) identify the types of AI-powered online learning interactions that influence consumer engagement and decision-making; (2) develop a model of factors influencing consumer purchase decisions in AI-powered online learning interactions, focusing on the roles of perceived enjoyment and perceived co-creation; and (3) elucidate the mediating role of co-creation in the relationship between AI-powered online learning interactions and consumer purchase intention. This framework aims to provide a comprehensive understanding of how AI-driven technologies reshape online learning experiences and their subsequent effects on consumer behaviour.

It is evident that AI-driven online study interactions, including those among learners, content, instructors, and peers, have a significant positive influence on consumers' purchase intentions. This effect is mediated by learners' perceived enjoyment and perceived co-creation, which play a substantial and partial mediating role in the relationship between AI-powered online learning interactions and purchase intentions. Online learning environments that foster enjoyment and co-creation not only have a direct impact on purchase intentions but also exert indirect effects through AI-powered interactions. These findings contribute significantly to the existing literature and provide a foundation for further research on online courses from marketing and business perspectives, offering valuable guidelines to industries and practitioners. This study, therefore, aims to enhance understanding of how AI shapes customer behaviour within online learning environments and to provide theoretical and practical insights in this rapidly evolving field.

Theoretical Framework and Hypothesis Development

AI-Powered Online Learning Interaction

Moore (1989) argues that interaction is a critical concept with multiple meanings in distance education and classifies online interaction into three primary categories: learner-content, learner-instructor, and learner-learner interaction. Moore (1989) transactional interaction model remains one of the most widely cited and adopted frameworks for examining the dynamics of distance education (Lin & Wang, 2024). However, the advent and integration of AI in online education have significantly transformed these interactions. For instance, in learner-content interaction, AI adapts to students' abilities, interests, and activities, delivering tailored content and independently generating learning materials or recommending suitable resources to enhance learning experiences (Williamson & Eynon, 2020). AI systems can also autonomously grade assignments and exams, analyse written work, and provide detailed feedback (Seo et al., 2021). In terms of learner-learner interaction, AI fosters collaborative learning environments where students can share knowledge and engage in teamwork (Zawacki-Richter et al., 2019). Accordingly, this study adopts Moore's interaction model as its theoretical framework, focusing on three categories of AI-powered online learning interactions: (1) AI-powered learner-content interaction, (2) AI-powered learner-instructor interaction, and (3) AI-powered learner-learner interaction.

AI-powered Online Learning Interaction and Perceived Enjoyment

Perceived enjoyment reflects the extent to which the use of a technology or system is regarded as enjoyable (Davis et al., 1992). In the context of AI-driven online learning, intelligent adaptive systems enhance students' learning outcomes and significantly increase their enjoyment of the learning process. This heightened satisfaction can be attributed to the improved alignment between learning content and individual needs and interests. Interactions with AI provide immediate feedback, which bolsters learners' motivation to engage further. The perceived effectiveness and usefulness of these AI-driven interactions contribute to greater enjoyment and an increased willingness to utilise AI for learning purposes (J. Li et al., 2024). Additionally, AI facilitates personalised learning by matching learners with compatible learning partners based on shared interests, learning styles, and goals. On learning platforms, AI identifies common interests and recommends relevant topics, fostering more meaningful and enjoyable interactions among learners. These features allow learners to experience a stronger sense of fit and enjoyment in their interactions. Based on these insights, the following hypotheses are proposed:

H1a: *Learner-content interaction powered by artificial intelligence positively influences perceived enjoyment.*

H1b: *Learner-instructor interaction powered by artificial intelligence positively influences perceived enjoyment.*

H1c: *Learner-learner interaction powered by artificial intelligence positively influences perceived enjoyment.*

AI-Powered Online Learning Interaction and Perceived Co-Creation

Value co-creation refers to the activities that autonomous participants engage in to develop value through interaction. Enhanced evaluation of consumer behaviour and improved communication innovations have provided a platform for greater consumer engagement. In this context, customer value is co-created through interactions with artificial intelligence services (Lalicic & Weismayer, 2021). Communication is central to this process, thereby enhancing the learning experience (John & Supramaniam, 2024). Since the rise of AI technologies, consumers have benefited from increased convenience and speed. AI-driven online learning can create personalised materials, intelligent training, and effective interactions, thus enhancing learner engagement (Huang et al., 2024; Williamson & Eynon, 2020). The following hypotheses are therefore proposed:

H2a: *Learner-content interaction powered by artificial intelligence positively influences perceived co-creation.*

H2b: *Learner-instructor interaction powered by artificial intelligence positively influences perceived co-creation.*

H2c: *Learner-learner interaction powered by artificial intelligence positively* *influences perceived co-creation.*

The Perceived Enjoyment and Purchase Intention

The enjoyment, pleasure, or satisfaction consumers derive from using a product or service can positively impact their purchase intention, a relationship well-established in online purchasing contexts such as mobile shopping, AR-driven purchases, and social media platform transactions (Natarajan et al., 2017; Smink et al., 2019; Zhang et al., 2023). AI significantly enhances perceived enjoyment by offering personalised and entertaining content, as well as fostering improved social interactions. This not only strengthens brand loyalty but also encourages more favourable consumer behavior (Huang et al., 2024; Kumar et al., 2024). Consequently, the following hypothesis is proposed:
H3: *Perceived enjoyment has a positive effect on purchase intention*

The Perceived Co-Creation and Purchase Intention

Value co-creation in virtual environments is facilitated by customer-driven technology platforms and activities initiated by companies or customers that generate value (Zwass, 2010). It is a collaborative, social, and innovative process involving stakeholders and organisations, yielding mutual benefits and value for all parties (Ind et al., 2013). The co-creation model, particularly evident in social network marketing, significantly influences consumers' purchasing behavior (Arbabi et al., 2022; See-To & Ho, 2014). AI enhances consumers' sense of participation by personalising the co-creation process, which in turn boosts their purchase intention (Chandra & Rahman, 2024). Therefore, the following hypothesis is proposed (Figure 1).
H4: *Perceived co-creation positively influences purchase intention.*

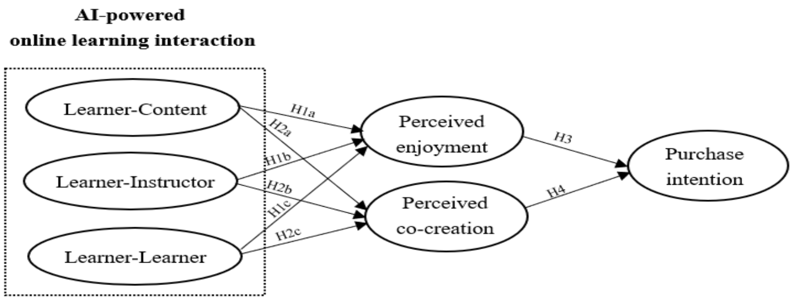

Figure 1: *Research Model*

Methodology

Data Collection and Sample Characteristics

Our research adopted a quantitative approach, employing questionnaires distributed via "Wenjuanxing," a prominent online survey platform in China with over 6.2 million registered users, covering various regions, ages, education levels, and occupations. To ensure reliability, validity, and generalisability, the platform enforces strict user registration and verification, preventing multiple submissions from the same IP address. In recent years, Wenjuanxing has gained increasing use in academic research related to psychology, management, medicine (Jin et al., 2022; Ning et al., 2020), and consumer behavior (Y. Li et al., 2024; Xue et al., 2023). The pre-tested questionnaire was reviewed by three groups of subject matter experts to ensure content validity and clarity. Due to time constraints and a lack of experience with Camtasia for creating screen and audio recordings of online learning activities, a pilot test was conducted with a sample of online learners to identify and correct any potential language or technical errors. The target population consisted of users who purchased online courses created with AI tools, focusing on individuals aged 18 and above.

Table 1: *Demographic Information of Participants*

Measure	Items	Frequency	Percentage (%)
Gender	Male	223	52.2
	Male	204	47.8
Age	18–24 Years Old	95	22.2
	25–34 Years Old	220	51.5
	35–44 Years Old	97	22.7
	45 Years Old or Above	15	3.5
Education Status	Junior College	50	11.7
	Bachelor Degree	308	72.1
	Master Degree or Above	69	16.2
Occupation	Student	41	9.6
	Company Employee	292	68.4
	Educator	38	8.9
	Government Employee	28	6.6
	Self-Employed	28	6.6
Monthly Income	Below RMB 5,000	117	27.4
	RMB 5,000-9,999	158	37
	RMB 10,000-14,999	103	24.1
	Above RMB 15,000	49	11.5
Online Course Experience	Less than 6 Months	106	24.8
	6-12 Months	103	24.1
	More than 1 Year	121	28.3
	1-2 Years	48	11.2
	More than 2 Years	49	11.5
Frequency of Attending Online Courses	Once or Twice Every Month	81	19
	Three to Four Times Every Month	171	40
	Five to Six Times Every Month	92	21.5
	More than 6 Times Every Month	83	19.4
Time Spent Per Online Course Session	Less than Half an Hour	47	11
	30 Minutes and 1 Hour	210	49.2
	1 to 2 Hours	156	36.5
	2 Hours and More	14	3.3

Participants voluntarily completed the questionnaire via an online link. To ensure sample validity, the first section included two screening questions: whether the participant had purchased an online course and whether it used AI technology. Only those who answered affirmatively to both questions could proceed. Participants who completed the questionnaire received a 10-yuan reward. Based on Cochran's formula, a sample size of approximately 384 was recommended for an infinite population size (Cochran, 1977). In this research, 470 questionnaires were collected. After eliminating those with abnormal IP addresses or completion times under 90 seconds or exceeding 1000 seconds, 427 valid questionnaires were retained, yielding an efficient rate of 90.85%. Of the 427 participants, 52.2% were male and 47.8% female, indicating a slight male majority. Age distribution was centred on the 25-34 age group (51.5%) and the 18-24 group (22.2%). Most participants held a bachelor's degree (72.1%), with 16.2% possessing a master's degree or higher. In terms of occupation, 68.4% were company employees, and 9.6% were students. Monthly income was predominantly between 5000-9999 RMB (37%), followed by under 5000 RMB (27.4%). Regarding online course experience, 28.3% had over a year of experience, while 24.8% had less than 6 months and 24.1% had 6-12 months. Most participants engaged in online courses 3-4 times a month (40%), with 21.5% attending 5-6 times. The typical duration of participation was 30-60 minutes (49.2%) or 1-2 hours (36.5%). Detailed data are provided in Table 1.

Measures

The research questionnaire is structured into two sections. The first section gathers basic participant information, including gender, age, education level, occupation, monthly income, and the duration and frequency of online course engagement. This data will be used for descriptive statistical analysis. The second section contains the core measurement scales.

Table 2. *Demonstrates Variable Questionnaire Information*

Variables	Dimensions	Number of Items	Source
AI-Powered Online Learning Interaction	Learner-Content Learner-Instructor Learner-Learner	4 4 4	(Moore, 1989; Williamson & Eynon, 2020)
Perceived Enjoyment		3	(Huang et al., 2024)
Perceived Co-Creation		3	(Jimenez-Barreto & Campo-Martinez, 2018; Pourjahanshahi et al., 2023)
Purchase Intention		3	(Yin & Qiu, 2021; Zhou et al., 2022)

The antecedent variable is AI-powered online learning interaction, divided into three categories based on Moore's interaction theory and AI's application in online education: AI-powered learner-content, instructor, and peer interaction, each measured by four items. The mediating variables are perceived enjoyment and perceived co-creation, both measured by three items. The outcome variable is purchasing intention, measured by three items. In total, the scale comprises 21 items across six variables. All items were adapted from established studies, incorporating Moore's interaction theory and AI characteristics in online education. A 7-point Likert scale (1 = strongly disagree, 7 = strongly agree) was used for scoring. The questionnaire information for each variable is detailed in Table 2.

Data Analysis Method

This research employs SPSS and Amos software for data analysis, following a series of sequential steps. First, descriptive statistics are performed on the demographic data from the first section of the questionnaire. Next, reliability and validity tests are conducted on the scale sample data from the second section to confirm the measures' credibility. A structural equation model is then developed to test the hypotheses and explore mediating effects. Finally, overall and multi-group path coefficient analyses of the theoretical model are performed to validate the results of each hypothesis.

Results

Reliability and Validity Measures

Second-section main scale tests were performed. Table 3 shows that all item factor loadings were above 0.7, indicating a significant link between constructs and items (Fornell & Larcker, 1981). This ensures that items accurately reflect structures. Each construct had a Composite Reliability (CR) above 0.8, exceeding the 0.7 threshold, suggesting strong internal consistency among items (Fornell & Larcker, 1981). These results confirm measurement model dependability. Table 3 shows the Average Variance Extracted (AVE) and CR values for convergent validity. AVE > 0.5 and CR > 0.7 were met for all convergent validity metrics, suggesting satisfactory validity (Fornell & Larcker, 1981).

Table 3: *Demonstrates Measurement Model*

Construct	Item	Factor Loading	CR	AVE
Learner-Content			0.894	0.678
LC1	AI tools make accessing learning content more convenient	0.843		
LC2	The AI system provides personalized learning resources and content based on my progress and preferences	0.806		
LC3	With the help of AI, I can actively learn the relevant content instead of passively receiving it	0.823		
LC4	AI technology helps me better understand course content and identify key knowledge points	0.820		
Learner-Instructor			0.887	0.661

Construct	Item	Factor Loading	CR	AVE
LI1	AI technology enhances my communication with teachers	0.818		
LI2	I can ask teachers questions through AI tools and receive timely responses	0.810		
LI3	AI technology allows teachers to better adjust to my learning needs	0.804		
LI4	AI technology makes my interactions with teachers more engaging and personalized	0.821		
Learner-Learner			0.891	0.672
LL1	The AI system helps me find peers with similar learning interests	0.842		
LL2	AI technology strengthens my communication with other learners	0.824		
LL3	AI tools make collaboration with another learners smoother	0.779		
LL4	AI technology fosters connections between learners, helping to create a learning community	0.833		
Perceived Enjoyment			0.889	0.728
PE1	AI-powered online learning is fun for me	0.846		
PE2	AI-powered online learning makes me feel pleasant	0.861		
PE3	AI-powered online learning feels entertaining to me	0.853		
Perceived Co-Creation			0.884	0.717
PC1	AI technology increases my engagement in learning, making me more likely to participate in AI-powered online courses	0.855		
PC2	With AI support, I am more likely to share my learning experiences and ideas with others on the platform	0.837		
PC3	With AI support, I am better able to create learning experiences for myself and others	0.848		
Purchase Intention			0.889	0.728
PI1	The application of AI technology increases my intention to purchase online courses	0.850		
PI2	I would consider purchasing AI-powered online learning courses	0.866		
PI3	I am willing to purchase online courses that use AI technology	0.843		

Table 4 compares the square root of the AVE for each construct to the inter-construct correlations. Fornell and Larcker (1981) define discriminant validity as a construct's square root of AVE being greater than its correlations with other constructs. Table 4 shows that all construct correlation coefficients are smaller than their AVE square roots, indicating that each construct is more tightly associated to its own indicators than to others. As seen in Table 4, all constructs in this investigation had excellent discriminant validity.

Table 4: *Demonstrates the Discriminant Validity*

	LC	LI	LL	PE	PC	PI
LC	**0.823**					
LI	0.417	**0.813**				
LL	0.384	0.508	**0.820**			
PE	0.420	0.429	0.413	**0.853**		
PC	0.347	0.424	0.412	0.356	**0.847**	
PI	0.339	0.388	0.388	0.345	0.250	**0.853**

Note: On-diagonal elements(bold) are the square root of the AVE values.

To mitigate common method bias, our study masked the variable names during the questionnaire design and conducted Harman's single-factor test (Podsakoff et al., 2003). Factor analysis without rotation, based on the questionnaire items, revealed that the highest factor explained 36.01% of the variance. This indicates that there is no significant general approach bias in the data.

Structural Model Analysis

Amos was utilised to formulate structural equations for model fit testing, with seven indicators selected for fit analysis: CMIN/DF, GFI, AGFI, CFI, TLI, IFI, and RMSEA. The analysis produced the following results: CMIN/DF = 1.402; GFI = 0.948; AGFI = 0.933; CFI = 0.987; TLI = 0.985; IFI = 0.987; RMSEA = 0.031. These fit test results indicate that CMIN/DF is below 3, GFI, AGFI, CFI, TLI, and IFI exceed 0.9, and RMSEA is under 0.05, suggesting that all indicators fall within acceptable ranges, confirming a good model fit (Bagozzi & Yi, 1988). Hypotheses were tested using standardized path coefficients and significance levels (p-values) to assess the proposed relationships between constructs. As shown in Figure 2 and Table 5, the results demonstrate that all paths have p-values less than 0.01, indicating statistical significance and providing support for the proposed model. Specifically, the three latent variables of AI-powered online learning interaction—learner-content interaction (LC), learner-instructor interaction (LI), and learner-learner interaction (LL)—all have significant positive effects on perceived enjoyment (PE), thus supporting hypotheses H1a, H1b, and H1c. Additionally, LC, LI, and LL significantly and positively influence perceived co-creation (PC), confirming hypotheses H2a, H2b, and H2c. Furthermore, both perceived enjoyment (PE) and perceived co-creation (PC) significantly and positively impact purchase intention (PI), supporting hypotheses H3 and H4 (Table 5).

Table 5: *Demonstrates the Hypotheses Results*

Hypothesis	Path	Standardized Path Coefficients	P-Value	Result
H1a	LC → PE	0.252	< 0.001	Validated
H1b	LI → PE	0.228	< 0.001	Validated
H1c	LL → PE	0.212	< 0.001	Validated
H2a	LC → PC	0.162	0.004	Validated
H2b	LI → PC	0.246	< 0.001	Validated
H2c	LL → PC	0.232	< 0.001	Validated
H3	PE → PI	0.310	< 0.001	Validated
H4	PC → PI	0.163	0.003	Validated

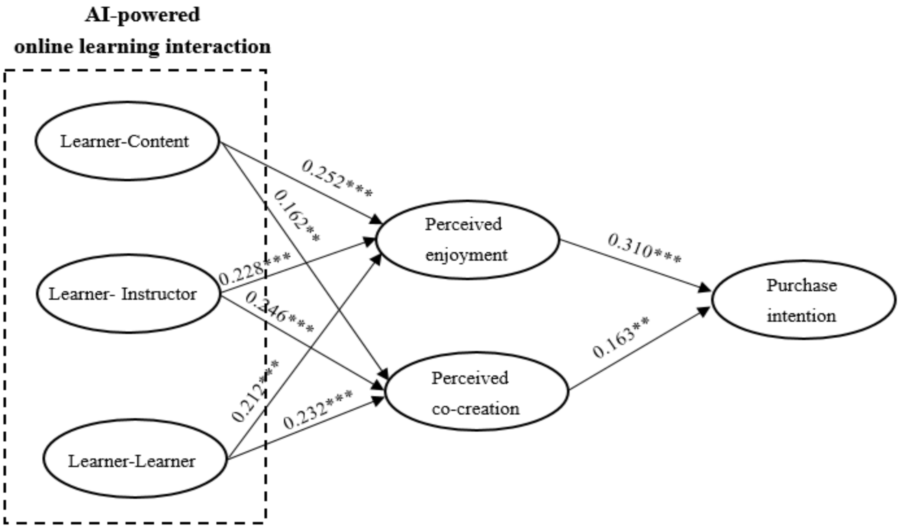

Figure 2: *Structural Results (*** represents p < 0.001; ** represents p < 0.01)*

Test of Mediating Effects

Researchers examined the mediating roles of PE and PC between the antecedent variables of AI-powered online learning interaction (LC, LI, LL) and the outcome variable, PI. Initially, direct paths from LC, LI, and LL to PI were included in the model. To assess the mediating effects of PE and PC, the bootstrapping method with 5,000 samples was employed, and the bias-corrected confidence intervals were analysed. The results showed statistically significant indirect effects, with 95% confidence intervals not containing zero, as shown in Table 6. Specifically, AI-powered online learning interaction (LC, LI, LL) significantly mediated purchase intention through perceived enjoyment and co-creation. Additionally, all pathways displayed partial mediation, indicating that LC, LI, and LL influence PI both indirectly through PE and PC, and directly. Therefore, perceived enjoyment and perceived co-creation moderate these relationships, highlighting the importance of these mediating variables between AI-based online learning interaction and purchase intention.

Table 6: *Mediation effect results*

			Bias-Corrected 95%CI	
Path	**Indirect Effect**	**P-Value**	**Lower**	**Upper**
LC→PE→PI	0.108	< 0.001	0.057	0.183
LC→PC→PI	0.055	< 0.001	0.014	0.116
LI→PE→PI	0.102	< 0.001	0.053	0.175
LI→PC→PI	0.048	< 0.001	0.001	0.118
LL→PE→PI	0.095	< 0.001	0.050	0.161
LL→PC→PI	0.046	< 0.001	0.003	0.110

Discussion

Theoretical Implications

This study integrates Moore's three categories of interaction theory in education with co-creation value theory to develop a conceptual framework analysing the connection between AI-powered online learning interactions and consumer purchase intention. The study confirms all hypotheses, offering novel insights into the role of artificial intelligence in online learning interactions and user behaviours. Through examples, we illustrate how AI enhances customer engagement and drives purchase behaviours through interaction and co-creation. Building on prior interaction theory literature (Moore, 1989), this research defines and examines AI-enabled online study interactions, focusing on purchase intention. Our findings show that AI technology plays a critical role in interactions between content and learners, instructors and learners, and among learners themselves. These AI-powered interactions not only improve the learning experience but also significantly influence purchase intentions by enhancing perceived enjoyment and co-creation. This supports prior research that interaction is key in value co-creation (John & Supramaniam, 2024; Ribeiro et al., 2023) and confirms its relevance in online education. Thus, our study demonstrates how AI facilitates purchase intentions through interaction, providing strong theoretical support for course design and operation on online education platforms.

Interestingly, the AI-powered learner-content interaction had a smaller effect on perceived co-creation compared to other interaction types. The standardized path coefficient for learner-content interaction was 0.162, which, while statistically significant ($p = 0.004$), was lower than the learner-instructor interaction (standardized path coefficient = 0.246, $p < 0.001$) and the learner-learner interaction (standardized path coefficient = 0.232, $p < 0.001$). This suggests that while AI adds value through personalised content recommendations, content interaction plays a less significant role in fostering co-creation compared to interactions with instructors and peers. This may be due to content interaction typically involving a unidirectional transfer of information, lacking the collaboration and in-depth interaction needed to stimulate a strong sense of co-creation. In contrast, interactions with instructors and peers provide more feedback, guidance, and opportunities for collaboration, thereby enhancing the co-creation experience (Chandra & Rahman, 2024; Seo et al., 2021). Consequently, despite the support of AI, learner-content interaction appears less effective in promoting co-creation value.

Regarding the impact of perceived enjoyment and co-creation on purchase intention, perceived enjoyment had a more significant effect on shopping intention (standardized path coefficient = 0.310, $p < 0.001$), while perceived co-creation had a relatively weaker influence (standardized path coefficient = 0.163, $p = 0.003$). This suggests that in an AI-powered online educational environment, a learner's purchase decision is more strongly influenced by enjoyment and emotional satisfaction rather than the co-creation process. AI enhances learners' enjoyment through personalised content and immediate feedback, with direct emotional gratification playing a more crucial role in driving purchase decisions (Huang et al., 2024; J. Li et al., 2024).

The key findings of the study reveal that PE and PC significantly mediate the relationships between the three dimensions of AI-powered online learning interaction (LC, LI, LL) and PI. The indirect effects of LC→PE→PI, LI→PE→PI, and LL→PE→PI were statistically significant, with values of 0.108 ($p < 0.001$), 0.102 ($p < 0.001$), and 0.095 ($p < 0.001$), respectively, emphasising the strong mediating role of perceived enjoyment across all interaction types. In contrast, the indirect effects through perceived co-creation were weaker: LC→PC→PI (0.055, $p < 0.001$), LI→PC→PI (0.048, $p < 0.001$), and LL→PC→PI (0.046, $p < 0.001$).

While perceived co-creation mediated the relationships in all three types of interactions, it was found to be a weaker driver of purchase intention compared to perceived enjoyment. This could be attributed to learners deriving pleasure from personalised learning experience and immediate feedback in an AI-powered online environment, while the experience of co-creation is more indirect. This distinction is noteworthy, as current research often emphasises the technological aspects of AI-powered online learning rather than the interactive experiences of learners (Williamson & Eynon, 2020). This study highlights how AI-powered online learning interactions influence consumer purchase intentions through the mediating effects of perceived enjoyment and perceived co-creation. By emphasising these mediating mechanisms, we demonstrate the effectiveness of AI-powered learning interactions in enhancing learner enjoyment and engagement, thus driving consumption behaviour.

Practical Implications

This study offers several practical recommendations. Firstly, AI-powered online learning interactions significantly influence learners' perceived enjoyment and co-creation, which in turn impacts their purchase intentions. The results indicate that LC, LI, and LL interactions particularly affect perceived enjoyment, highlighting the enriching and engaging nature of AI-supported online education. These interactions enhance pleasure, which drives learners' intentions to purchase online course products. Additionally, AI supports learner-learner and teacher-learner interactions by improving the quality of learning interactions and fostering co-creative learning, thereby boosting purchase intentions

To make online courses more purposeful, engaging, and enjoyable, educators should focus on creating content that aligns with learners' perceived enjoyment and co-creation. Incorporating AI technology into course design, offering personalised approaches, real-time feedback, and dynamic scenarios can help prevent stagnation. Enhancing interactivity, providing more feedback, and increasing human-computer interaction can foster co-creative learning and positively influence purchase intentions. Designers should also break learning into group tasks and encourage timely collaboration, making the learning environment more enjoyable and fulfilling. Online platforms can enhance teacher-learner and peer collaborations, stimulating interest in co-creation and course appeal. The development of AI-based collaboration tools and intelligent discussion platforms can further improve learners' sense of participation and accomplishment.

Organizations must continue investing in AI to foster highly personalized and interactive delivery through online learning platforms. As an avenue for further research into users' perceptual experiences, companies can establish robust methods, such as periodic surveys of learners, and consistently fine-tune AI systems and learning content using big data analytics strategies. Education experts should focus on enhancing perceived enjoyment by incorporating additional attributes, while co-creation with users can improve user loyalty and contribute to long-term returns. Moreover, further investments should be made to integrate AI technology in a way that addresses learners' needs and elevates service quality. Consumers should place greater emphasis on how platforms can offer interactive and co-creative online courses. By engaging in group discussions and benefiting from AI-generated learning recommendations, learners will be able to actively participate in platform-based activities, thereby boosting both their learning outcomes and perceived satisfaction. This interaction will help learners gain a clearer understanding of the learning environment, enhance their educational experience, and provide valuable feedback for the design of future courses. In conclusion, the future of online education should be driven by AI technology to meet learners' expectations, offering diverse, interactive, and immersive learning experiences.

Limitations and Future Research Directions

Despite providing valuable insights into AI-powered online learning interactions and their impact on purchase intention, our study has several limitations. Firstly, data was only collected from one country, China, which limits the generalizability of the results to other regions or demographics. Future research should replicate the study in different cultural and socioeconomic circumstances to improve relevance. Second, the study used questionnaires. Anonymous data collection and Harman's single factor test reduced bias, but technique variance may remain. To confirm AI-powered interactions and purchase intentions, future study could use objective behavioural data like online course purchases or data scraping. Moreover, the study focused on the mediating roles of perceived enjoyment and perceived co-creation, but other factors, such as trust in AI, perceived ease of use, and perceived usefulness, may also influence purchase decisions in AI-powered environments. Future research should explore these additional variables to deepen our understanding of AI-customer interactions. Furthermore, while this study concentrated on AI in online education, its impact on purchase intention could extend to sectors like healthcare, retail, or finance. Expanding the theoretical framework to other industries would provide a broader perspective on AI's influence on consumer behaviour. In conclusion, while this research offers a foundation for understanding AI's role in online learning and purchase behaviour, there is ample scope for further exploration, particularly in examining additional mediators and broadening its application across various industries.

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